International Journal of Research in Engineering, Science and Management
Volume-1, Issue-10, October-2018
www.ijresm.com | ISSN (Online): 2581-5792

Fusion of Structural and Textural Features for Melanoma Recognition

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***Abstract*—The biggest organ of the body is human skin. Its weight lies between six and nine pounds and surface area is about two square yards. Inner part of body is separated by skin from the outer environment. Melanoma is a type of cancer that mostly starts in pigment cells (melanocytes) in the skin. In order to increase diagnostic performance of melanoma, dermoscopy technique was introduced. Dermoscopy is a non-invasive skin imaging technique of acquiring a magnified and illuminated image of a region of skin for increased clarity of the spots on the skin. Dermatological diseases are the most prevalent diseases worldwide. This is being common, where the diagnosis is extremely complicated and requires improved experience in the domain. We use a dual stage approach which effectively combines Computer Vision on clinically evaluate histopathological attributes to accurately identify the disease. In the first stage, the image of the skin disease is identified to various types of pre-processing methods continued by feature extraction. The second stage involves the use of algorithms to identify diseases based on the histopathological attributes observed on analysing of the skin.**

***Index Terms*—Classification, Histopathological, Melanoma, Support vector machine.**

I. Introduction

Digital image processing handles with implementation of digital images with the help of a digital computer. Digital Image Processing is a subfield of signals and systems but focus particularly on images. They focuses on improving a computer system which is able to handle processing on an image. The input is a digital image and the system process that image by efficient algorithms, and produces an image as an output. The most common example is Adobe Photoshop. Digital Image Processing is one of the widely used application for processing digital images. Image processing basically includes the following three steps:

1. Providing the image with optical scanner or by digital photography.
2. Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not visible to human eyes like satellite photographs.
3. Output is the final stage in which result can be a modified image or else report that is based on image analysis.

In the support vector machine (SVM) classification method, three types of skin diseases were identified. Experimental results provides the requireable and feasibility of the proposed method.

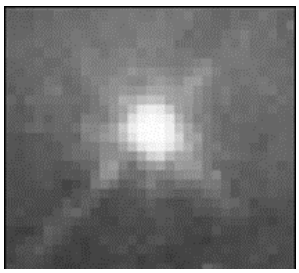
Fig. 1. Sample image

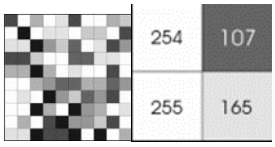

Fig. 2. Pixelized image

II. Related Work

We introduce related research for automatic benign and malignant skin lesion detection in the following.

Margarida Silveira, Dermoscopic images are detected using an intelligent agent-based or robotic system to conduct long-term automatic health monitoring and robust efficient disease diagnosis as autonomous e-Careers in real-world applications [1]. In this research, we aim to deal with such challenges by evaluating six methods for the segmentation of skin lesions in dermoscopic images. They includes some state of the art techniques which is being successfully used in many medical imaging complications (gradient vector flow (GVF) and the level set method of Chan et al. [(C-LS)]. They also provides a set of methods introduced by the authors which are combined with this certain application (adaptive thresholding (AT), adaptive snake (AS), EM level set [(EM-LS), and fuzzy-based splitand-merge ssss algorithm (FBSM)]. The segmentation methods has been applied to 100 dermoscopic images and they are further evaluated with their respective four different metrics, with the particular segmentation result they provides an experienced dermatologist as the ground truth. The best results were obtained by the AS and EM-LS methods, which

are semi-supervised methods. The fully automatic method is FBSM, where the results is slightly poor than AS and EM-LS.

Omar Abuzaghleh, a real time image analysis system [2] to aid in the malignant melanoma prevention and early detection is highly in-demand. In this paper, they proposed a real time image analysis system to recover the malignant melanoma prevention and their early detection. They present an image recognition technique, where the user will be able to capture skin images of different mole types and the system will analyze and process the images and inform the user at real-time to have a medical help urgently. This work introduces convenient steps for automating the process of melanoma prevention and detection. Experimental results on a PH2 dermoscopy research database images confirms the efficiency of the system.

III. The Proposed System

Proposed System, It is an intelligent decision support system for benign and malignant skin lesions classification. The system includes the following key stages, i.e. pre-processing, skin lesion segmentation, feature extraction and classification. We used eight different preprocessing algorithms, they are converting to grey scale image, sharpening filter, median filter, smooth filter, binary mask, RGB extraction, histogram and sobel operator. Figure 3 shows system architecture, which shows the principal processes of the proposed system. The test image is preprocessed, the RGB values of the images are extracted before converting it into a gray scale image. Sharpening filter is applied to the gray scale image in order to sharpen the details of the infected region. YCbCr was used to extract average colour code of the infected area from the binary image. The number of components of the skin affliction was extracted from the image using the Euler value. For the classification we will use GLCM (Gray Level Co-occurrence Matrix) and LBP (Local Binary Pattern). A threshold limit was imposed on the Euler value heuristically, exceeding which was an indicator of presence of a large number of inflictions. This is an important distinguishing feature characteristic for diseases. The Support vector machine classifier is already trained with the two set of features such as benign and malignant images. The test image features are given into the trained SVM model and the class will be recognized from the SVM. The following section describes the modules involved in the proposed work.

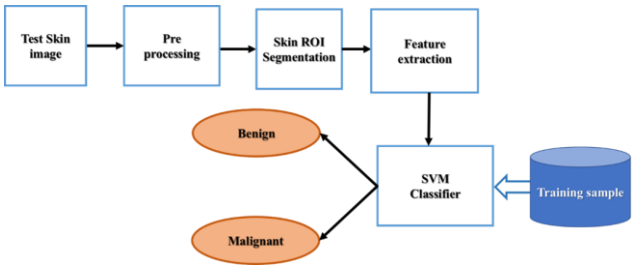

Fig. 3. Block diagram for proposed work

IV. Methods

A. Pre-Processing

A pre-processing method is essential for benign and malignant skin lesions classification. This involves transforming raw data into an understandable format for further processing. In the real world, data are often inconsistent and incomplete and may contain many errors. Removing any noise and unnecessary features which cause confusion to classifiers is required. The following pre-processing is conducted in this research.

1) Hair Remover

The Enhanced Dull Razor algorithm Fig. 4 was used to remove hairs from images where morphological closing image processing was generalized to grey-level images, followed by identification of the narrow, elongated hair outline.
Bilinear interpolation was implemented to substitute the identified pixels of the hairs. This step resulted in a smooth fill inward from the borders of the region of interest.

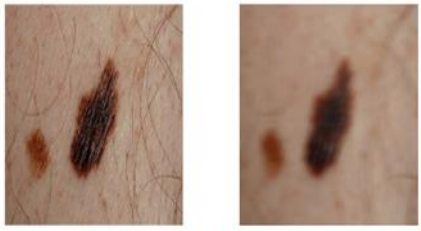

Fig. 4. Hair Removal Results; left (original image), Right (After hair removal)

2) Contrast Enhancement

Subsequently, the image clarity was enhanced by improving the shape and edges of the image. Image borders were sharpened using contrast enhancement. This process may also optimize subsequent segmentation accuracy.

3) Grayscale Conversion

RGB images of lesions, with M×N pixels in size, were transformed to grey scale by removing hue and saturation using a process which computes the weighted sum of the colour components.

B. Segmentation

Image segmentation is a technique to determine the shape and size of the border, and to separate the object from its background based on different features extracted from the image. After removing the noise from the lesion area, the lesion needs to be separated from the skin, and therefore the analysis for diagnosis is conducted purely using the necessary area.

Fig. 5. Segmentation results a) Original image b) Segmented lesion region

1) Adaptive Thresholding (AT)

Lesion segmentation can be obtained by comparing the color of each pixel with a threshold. The pixel is classified as active (lesion) if it is darker than the threshold. The output of this step is a binary image. Morphological post-processing is then applied to fill the holes and to select the largest connected component in the binary image. It was experimentally found that the blue component in the red-green-blue (RGB) representation is the one which allows the best discrimination in most dermoscopic images. However, there are a few exceptions. We have therefore used an automatic selection of the color component based on the entropy of the color component.

C. Feature Extraction

After segmentation, image features are extracted for the subsequent classification. Several methods have been identified for feature extraction. Overall, the majority of related work employed the ABCDE rules of dermatology for feature extraction. In this research, measurements such as compactness index, fractal index, and edge abruptness are used in order to indicate border irregularity.

1) Shape

a) Asymmetry: A melanocyte lesion may be diagnosed by a number of identifiers, of which one of the most significant is a lack of symmetrical morphology. In dermatology terms, the ABCDE rule model rates this aspect as the most crucial factor. In consideration of the symmetry feature, a number of factors are concurrently relevant, including color, texture and morphology. A three-fold classification system can be derived from measuring symmetry, with three-class outputs representing total symmetry, a lack of symmetry along a single axis and a lack of symmetry along dual axe, respectively. The lesion asymmetry was evaluated by calculating the area with inner and outer of the lesion, using the formula shown as follows.

$$AI = \frac{\Delta AK}{AL} * 100$$

Where AI represents asymmetry Index. ΔAK represents the area between the two halves of the lesion and AL denotes the lesion area.

b) Border Irregularity: Irregularities occurring in the edge of a malignant lesion offer useful information concerning that lesion's nature [5]. Typically, the edge of a malignant lesion usually exhibits four factors of interest, i.e. density, fractal dimension, radial variability and the extent to which its contour exhibits small irregularities. To identify the lesion border irregularity,

$$I = \frac{ab}{2\pi(a^2 + b^2)} \frac{P^2}{\Delta A}$$

Where I represent irregularity with a and b representing the lengths of major and minor axes of the lesions. P represents the perimeter of the lesion and ΔA indicates the area of corresponding.

c) Compactness: Another relevant feature is the degree to which the lesion can be described as compact. In order to determine this aspect, a comparative analysis is performed between the lesion's boundary and a circle with a circumference of the same length. It is the former of these two numerical values that presents a challenge in its assessment. One solution to this issue is to use the proportions of the most easily measured values of maximum and equivalent lesion diameter as defined in Equation below

$$C = \frac{4\pi P^2}{\Delta A}$$

2) Colour

The range of colour types utilized in diagnosing a melanocyte lesion can be broadly categorized into the following types: black, grey-blue, brown (dark), brown (light), red and white, which are indicators for a malignant skin lesion. The dermatological analysis allows for the determination of whether a colour category exists in a particular image and if so, where it exists [4]. This positional information is noted via a binary mask application, with image segmentation performed by the dermatological professional. In this paper, three type of colour space including HSV, RGB and LAB are used.

a*) Ratio of red, green and blue*: In the case of red, the ratio represents the average of the red constituent present in a lesion divided by the mean colour of the surrounding non-lesion skin. The ratio for red is expressed as follows:

3) Texture

The texture of a lesion can be estimated by a number of objective measures derived from Generalized Co-Occurrence Matrix (GCM).

a) Grey-Level Co-Occurrence Matrix (GLCM): It has been intensively used as a widely-adopted and popular methodology. GLCM provides a number of numerical assessment measures, which are employed in this research with each being grey-level shift-invariant in nature. These enable sensitive linear shift recognition in terms of the intensity of illumination, such that texture can be categorized in these terms. Research [18] has demonstrated that a particular point exists beyond which an elevated G value leads to reduced ability to differentiate in disparity and contrast, despite maintaining an even level of the other measures[9]. So as to populate a matrix with a sufficient level of data, an equal quantization to 64 grey levels was carried out, with this number being above a lower bound of 24 and selected based on the findings of existing studies [7].Such low values do, in addition, minimize the impact of image noise.

It is recommended that the GCM after normalisation presents a strong level of density, so as to provide confident statistical estimation within the distribution of joint probability [10]. In this research, the measures consist of three color space (RGB, HSV, LAB) to reduce the impact of deference lighting before

the color extraction, plus six color pair (RR, RG, RB, GG,GB, BB). Three grey level quantizations, i.e. 64, 128, 256, are used for every color space. The 12 texture features represent autocorrelation, correlation, cluster prominence, dissimilarity, entropy, energy, maximum probability, contrast, homogeneity, cluster shade, inverse difference moment and variance as mentioned in Haralick [19] and six inter-pixel distances.

b) Local Binary Pattern: The LBP operator was first introduced as a complementary measure for local image contrast (Harwood et al. 1993, Ojala et al. 1996). The first incarnation operator worked with the eight-neighbors of a pixel, with the value of a center pixel as a threshold. An LBP code for a neighborhood was introduced by multiplying their thresholded values with their weights given to the pixels, and combining up the result. Whereas the LBP was, invariant to monotonic changes in gray scale and it was implemented by an orthogonal measure of their local contrast. The average gray levels falls below the center pixel is decreased from the gray levels above (or equal to) the center pixel. Two-dimensional distributions of the LBP and their local contrast measures are used as features. The operator is LBP/C, and they are very good discrimination whose rates were reported with textures.

D. Support Vector Machine Classifier

Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection. More formally, a support vector machine constructs a hyper-plane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks [6]. Intuitively, there is a good separation is accompanied by the hyper-plane with the largest distance to the nearest training-data point of any class (so-called functional margin), the large margin and their low generalization error of the classifier.

E. SVM Algorithm

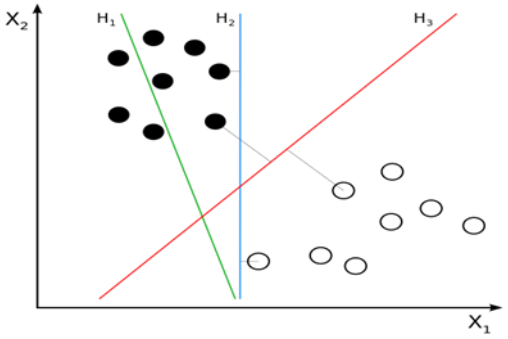

Fig. 6. Linear separable patterns

Classification of data is a common work in machine learning techniques. Where some of the data points belong to one of two classes, and their goal is to make decision to which class a new data point will have to go. In the case of support vector machines, a data point is viewed as a p-dimensional vector, and we want to know whether we can separate such points with a (p-1)-dimensional hyper-plane. This is called a linear classifier [6]. Multiple hyper-planes are used classifying the data. One way to choose the best is as the best hyper-plane is the one that represents the largest separation, or margin, between the two classes. Finally we choose the hyper-plane with the distance nearest to the data point on each side and is maximized.

V. Experimental Results

The test images are collected form the online database called university of Lowa health care. This work constitute the recognition different skin cancer disease automatically. The test images are differing from each other on the way of texture, color and shape. The following figure depicts the skin diseases which are considered in this work.

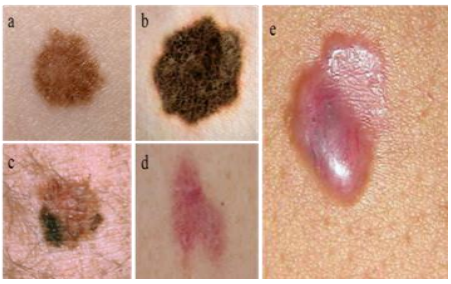

Fig. 7. Sample images

If such a hyper-plane is found, it is the maximum-margin hyper-plane and their linear classifier is known as the maximum margin classifier; or equivalently, the perception of optimal stability. This work is implemented with total number of 45 skin cancer images.

The Fig. 7 shows the result of SVM classifier. Table-1 show automatic image classification system. The Fig.7 is used to classify the GUI that displays what the type of skin cancer was.

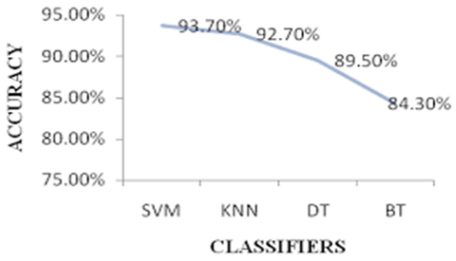

Fig. 8. Analysis graph

Early melanoma skin cancer diagnostic system using computer based techniques is more efficient than the conventional Biopsy methods. The cost involved as well as the time taken for detection is less in this proposed methodology. The methodology incorporates artificial intelligence and digital image processing for skin cancer detection. SVM based classifier proved to be very efficient in decision making as well as pattern recognition applications. The proposed method has an accuracy of 98% for recognition melanoma skin cancer (benign & malignant) and 93% for recognition malignant melanoma types, which is much higher than that of

conventional methods.

TABLE I
OVERALL FEATURE MATRIX

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Label
1	60.2330 3	182.8191	149.0223	25	130.6915	211	211	3327.697	5851 2	2.34E+09	671 46.78	28.23	1.71E-05	225 74.62	-1.06E-05	carcinoma
2	120.0061	211.0782	166.4309	25	165.8384	139	139	211 5.108	24500	6.22E+08	282 21.9	28.23	4.08E-05	438 5.03	1.73E-05	carcinoma
3	33.60273	194.022	154.5049	25	127.3766	265	265	3924	8655	4.08E+09	993 43.2	28.23	1.15E-05	624.9481	9.80E-07	carcinoma
4	44.8917 7	201.8549	170.348	25	139.0315	105	105	2376	2079 0	5.93E+08	239 21.1	28.23	4.81E-05	341 4.171	-1.95E-05	carcinoma
5	189.5286	196.3504	141.254	25	175.711	191	191	252 2.136	4014 4	1.21E+09	461 65.26	28.23	2.49E-05	536 7.503	-9.11E-06	carcinoma
6	115.949	172.820	119.474	25	136.081	26	26	295 6.74	6603	2.34E+0	758 41.5	28.2	1.51E	487 6.62	-4.1	carcinom

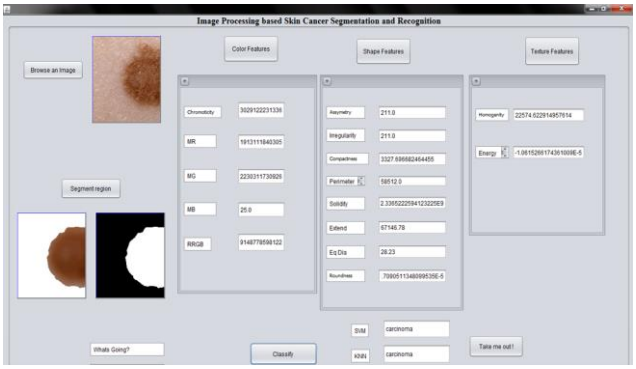

Fig. 9. Classification results on GUI

TABLE II
TEXTURE FEATURES OF DIFFERENT SKIN DISEASE.

	Contrast		Correlation		Entropy		Uniformity		Energy	
	Minimum	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum	Maximum
Normal skin	0.2053	0.3805	3.589	3.8917	1.0696	1.8224	3.8105	3.8974	843.7668	1437.6
Herpes	41.7036	178.2016	3.5308	3.7852	0.1355	0.5163	2.9878	3.6857	93.0058	345.2991
Paederus	51.676	87.3321	2.8167	3.2025	0.0741	0.1691	2.928	3.125	53.2181	121.5074
Psoriasis	8.713	40.3506	1.8612	3.6789	0.1849	0.5666	3.0617	3.4794	36.9206	205.6441

VI. CONCLUSION

The fusion of structural and textural features is explored for melanoma recognition. The structural features and the textural features are obtained from the different variants of LBP operator. The obtained results are also validated using SVM classifier. Melanoma is the dangerous type of skin cancer having highest mortality rate. Whereas, the annihilation in their early stage gives a high survival rate so that it demands early diagnosis. The accustomed diagnosis methods are expensive and inefficient due to the involvement of experienced experts with their requirements for the highly equipped environment. The recent advancements in the proposed system for this diagnosis are highly promising with improved accuracy and efficiency.

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